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CLASSIFICATIONS OF VOLTAGE STABILITY MARGIN (VSM) AND LOAD POWER MARGIN (LPM) USING PROBABILISTIC NEURAL NETWORK (PNN)

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ABSTRACT

Voltage stability margin (VSM) and load power margin (LPM) arethe indicators that show how close a load bus is to experiencing voltage instability. The smaller the values of VSM or LPM of a particular load bus, the closer the load bus towards voltage instability. This paper presents the application of probabilistic neural network (PNN) for classifying VSM and LPM values. A number of training data is generated for the PNN model to classify. The PNN model used in this paper should be able to classify which values are within VSM/LPM values and which values are not. The IEEE 14-bus system has been chosen as the reference electrical power system. MATLAB is used to deploy the PNN model for VSM and LPM classifications.

Keywords: voltage stability analysis, voltage stability margin, load power margin, artificial neural network, probabilistic neural network.

1. INTRODUCTION

Voltage stability margin (VSM) and load power margin (LPM) play a very important rolein the analysis of voltage instability. Both VSM and LPM can be used to determine the tendency of a particular load bus towards voltage instability. The smaller the values of VSM or LPM of a particular load bus, the closer the load bus towards voltage instability and vice versa. Voltage instability can cause one of the biggest problem in the field of electrical power system which is power system blackout [1], [2]. A power system is considered unstable whenever the power system is not able to maintain the voltage magnitude at all buses remain the same after the power system is being exposed to a disturbance [3]-[5].

Both VSM and LPM are obtained from power-voltage (PV) curve and reactive power-voltage (QV) curve. PV and QV curve is one of the famous methods in analysing voltage stability [1], [6]. These curves are produced by increasing the load of the power system for every load flow analysis. For every load flow analysis, the values load buses voltages and the values of real power (P) and reactive power (Q) of load are plotted as the PV and QV curve [3], [7], [8].

Artificial neural network (ANN) has been used by previous researches in the analysis of voltage instability. Most of the previous research used ANN to predict the values of voltage stability indices [8]-[11]. In this paper, both VSM and LPM values will be classified by using probabilistic neural network (PNN). A set of training data for VSM and LPM are generated. Then the values in the generated data will be classified using PNN.

2. METHODOLOGY

2.1 Voltage Stability Margin (VSM)/Load Power Margin (LPM)

Voltage stability margin (VSM) and load power margin (LPM) are defined as the distance between the normal/initial voltage/load power operating point until the voltage/load power critical/collapse point [12]. Both VSM and LPM can be divided into two categories which are VSM/LPM for real power of load (P) and for reactive power of load (Q). VSM (P), VSM (Q), LPM(P) and LPM (Q) are obtained from PV and QV curve as shown in Figure-1 [4], [5], [7], [8], [13]. It can be seen that the smaller value of VSM/LPM, the closer the bus of the power system towards voltage instability and vice versa. According to VSM and LPM definitions, Equation (1) until Equation (4) can be used for calculating VSM and LPM [7]:

VSM (P) = hypotenuse distance

$$|V_{initial}(P) - V_{critical}(P)| \quad (1)$$

where,

$V_{initial}$ (P) is the bus voltage at normal operating point (PV Curve)
$V_{critical}$ (P) is the bus voltage at voltage collapse point (PV Curve)

VSM (Q) = hypotenuse distance

$$|V_{initial}(Q) - V_{critical}(Q)| \quad (2)$$

where,

$V_{initial}$ (Q) is the bus voltage at normal operating point (QV Curve)
$V_{critical}$ (Q) is the bus voltage at voltage collapse point (QV Curve)

$$LPM(P) = (P_{critical} - P_{initial}) \quad (3)$$

where,

ARPN Journal of Engineering and Applied Sciences

$P_{critical}$ is the value of load (MW) at voltage collapse point
$P_{initial}$ is the value of load (MW) at normal operating point

$$LPM\ (Q) = (Q_{critical} - Q_{initial}) \quad (4)$$

where,

$Q_{critical}$ is the value of load (MVAR) at voltage collapse point
$Q_{initial}$ is the value of load (MVAR) at normal operating condition.

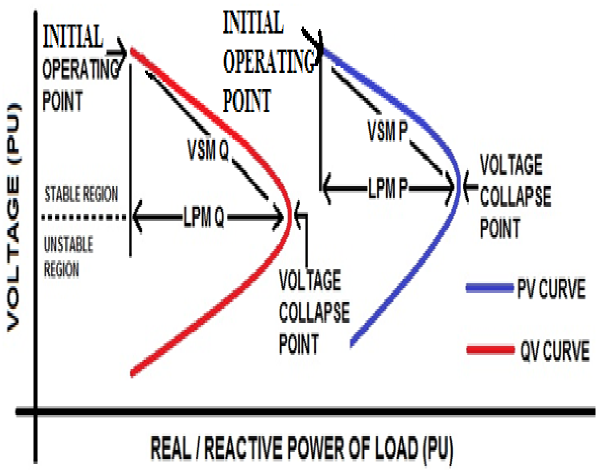

Figure-1. PV and QV curve.

2.3 Probabilistic Neural Network (PNN)

Probabilistic neural network (PNN) is used to classify the calculated values of VSM and LPM. According to [14], PNN is best used for classification purposes. Figure-2 shows the basic PNN structure [14]-[16].

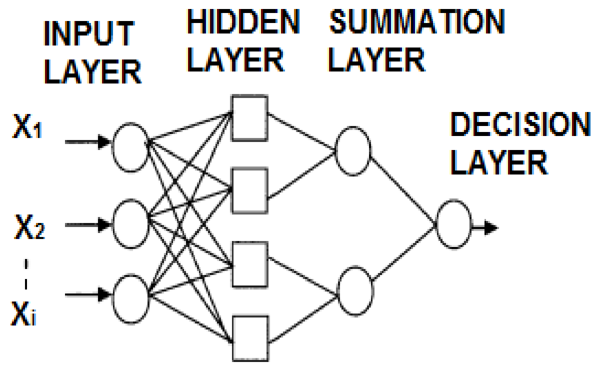

Figure-2. Basic PNN structure.

It can be seen from Figure-2 that PNN has four layers. The first layer which also known as input layer consists of the data that needs to be classified (calculated values of VSM and LPM). Then, the hidden layer calculates the distance measure between the input test case and the centre of training case represented by the neuron. In the summation layer, the density function of which class the hidden outputs layer belong to is estimated. Finally, at the decision layer, the class that obtains the higher probability in the summation layer are selected [14]–[16].

2.4 VSM/LPM Target classifications

In this research, the calculated values of VSM and LPM are divided into 3 classes. Values below the calculated VSM/LPM values are classified into Class 1. Values above the calculated VSM/LPM values are classified into Class 3. Class 2 consists the values that are under the range of ± 0.01 of the calculated VSM/LPM values. For example, if the calculated VSM value of a particular bus is 0.5, then other values that are below 0.49 and above 0.51 will be classified into Class 1 and Class 3, respectively.

2.5 Generation of training data

In order to generate the training data for both PNN, the values of real (P) and reactive power (Q) of load at load buses are varied randomly. In this research, the values of P and Q at load buses are varied within the range of -0.5 per unit until 1 per unit of the original base values [3], [8], [17]. 840 data were generated for this purpose.

2.6 The IEEE 14-bus system

Figure-3 illustrates the IEEE 14-bus system [18]. In this system, Bus 1 is the slack bus, Bus 2, Bus 3, Bus 6, and Bus 8 are voltage controlled buses, and the rest buses are load buses. Load buses are very important in voltage stability analysis because PV and QV curve are generated at load buses. The load flow analyses are done by using Power World Simulator software version 16.

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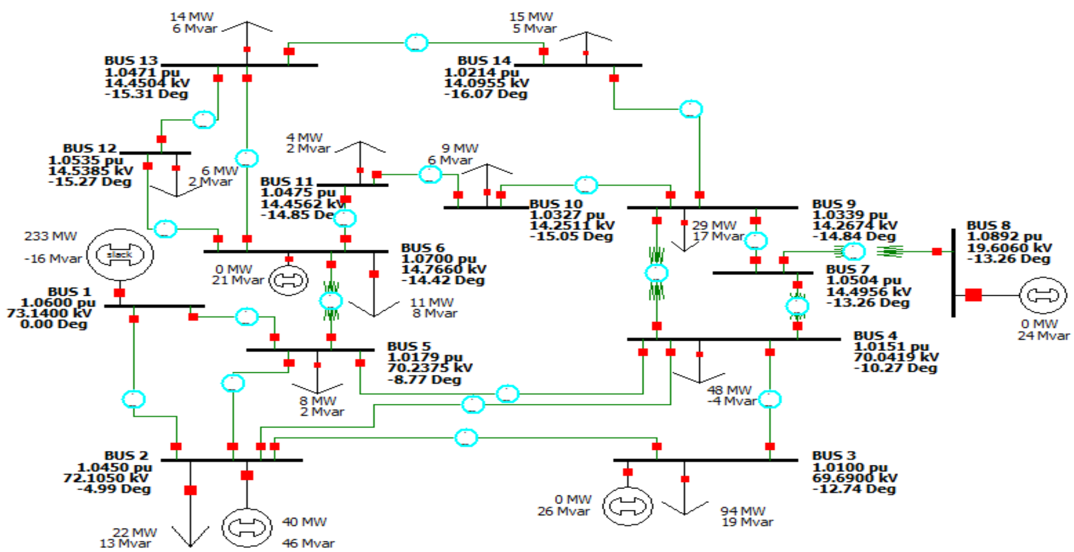

Figure-3. IEEE 14-bus system.

3. RESULTS AND DISCUSSIONS

3.1 VSM and LPM calculated values

Figure-4 shows the calculated values of VSM (P), VSM (Q), LPM (P) and LPM (Q) for the load buses in the IEEE 14-bus system. These values are calculated by using Equation (1)-(4).

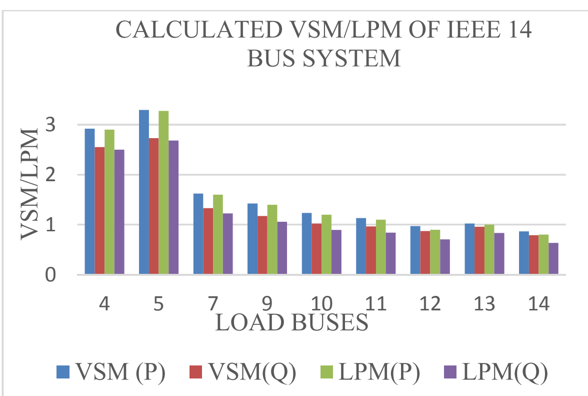

Figure-4. Calculated values of VSM (P), VSM (Q), LPM (P) and LPM (Q) for the load buses in the IEEE 14-bus system.

Figure-4 shows that Bus 12, Bus 13 and Bus 14 have low values of VSM and LPM with Bus 14 is the lowest. Hence, these three buses are more prone towards voltage instability. Figure-4 also depicts that Bus 4 and Bus 5 are top two most stable load buses in the IEEE 14-bus system.

3.2 Probabilistic Neural Network (PNN) classifications

PNN is used to classify the values of training VSM/LPM data (Section 2.5) into three classes as explained in Section 2.4. Since the number of generated training data is big, only the training data for the weakest bus (Bus 14) is displayed in Table-1 until Table-4.

Table-1. Results of Bus 14 VSM (P) Training data PNN classification.

VSM (P) Training data	Target classification	PNN classification
0.5017	1	1
0.4014	1	1
0.3011	1	1
0.2008	1	1
0.1004	1	1
0	1	1
0.103	1	1
0.2043	1	1
0.3063	1	1
0.4089	1	1
0.5136	1	1
0.6205	1	1
0.7319	1	1
0.8654	2	2
0.9084	3	3
0.8973	3	3
0.8888	3	3
0.8835	3	3
0.8803	3	3
0.8786	2	2
0.878	2	2

Table-2. Results of Bus 14 VSM (Q) Training data PNN classification.

VSM (Q) **Training data**	**Target Classification**	**PNN Classification**
0.5116	1	1
0.4088	1	1
0.3058	1	1
0.204	1	1
0.1021	1	1
0	1	1
0.1096	1	1
0.217	1	1
0.3263	1	1
0.4409	1	1
0.5624	1	1
0.6997	1	1
0.7897	2	2
0.8326	3	3
0.8554	3	3
0.8687	3	3
0.8775	3	3
0.8838	3	3
0.8889	3	3
0.893	3	3
0.8965	3	3

Table-3. Results of Bus 14 LPM (P) Training data PNN classification.

LPM (P) **Training data**	**Target Classification**	**PNN Classification**
-0.5	1	1
-0.4	1	1
-0.3	1	1
-0.2	1	1
-0.1	1	1
0	1	1
0.1	1	1
0.2	1	1
0.3	1	1
0.4	1	1
0.5	1	1
0.6	1	1
0.7	1	1
0.8	2	2
0.7546	1	1
0.6826	1	1
0.6251	1	1
0.5775	1	1
0.5367	1	1
0.5009	1	1
0.4691	1	1

Table-4. Results of Bus 14 LPM (Q) Training data PNN classification.

LPM (Q)	**Target classification**	**PNN classification**
-0.5	1	1
-0.4	1	1
-0.3	1	1
-0.2	1	1
-0.1	1	1
0	1	1
0.1	1	1
0.2	1	1
0.3	1	1
0.4	1	1
0.5	1	1
0.5973	1	1
0.637	2	2
0.63369	2	2
0.61595	1	1
0.59217	1	1
0.56756	1	1
0.54313	1	1
0.52083	1	1
0.49937	1	1
0.47902	1	1

It can be understood from Table-1 until Table-4 that PNN has successfully classified all of the generated VSM (P), VSM (Q), LPM (P) and LPM (Q) training data correctly as the target classification. It can be seen clearly that the training data values that have been classified into Class 2 (blue colour) are within ± 0.01 of the calculated VSM/LPM Bus 14 values. In Table-1, there are 3 values that are classified into Class 2. It is noticeable that every value in Class 2 is within ± 0.01 of the calculated VSM/LPM values. While in both Table-2 and Table-3, only one value is classified into Class 2. In Tables 4, 2 values are classified into Class 2.

ARPN Journal of Engineering and Applied Sciences

The results of PNN classification for VSM/LPM calculated values for all load buses are displayed in Table-5 until Table-8. Here, the classifying of the calculated VSM/LPM values for every load buses of the system are displayed.

Table-5. VSM (P) Classification by PNN.

BUS	VSM (P)	PNN Classification
4	2.9173	Class 2
5	3.2961	Class 2
7	1.6209	Class 2
9	1.4234	Class 2
10	1.2315	Class 2
11	1.1309	Class 2
12	0.9713	Class 2
13	1.0222	Class 2
14	0.8654	Class 2

Table-6. VSM (Q) Classification by PNN.

BUS	VSM (Q)	PNN Classification
4	2.5501	Class 2
5	2.7321	Class 2
7	1.3299	Class 2
9	1.1710	Class 2
10	1.0230	Class 2
11	0.9641	Class 2
12	0.8699	Class 2
13	0.9574	Class 2
14	0.7897	Class 2

Table-7. LPM (P) Classification by PNN.

BUS	LPM (P)	PNN Classification
4	2.9000	Class 2
5	3.2769	Class 2
7	1.6000	Class 2
9	1.4000	Class 2
10	1.2000	Class 2
11	1.1000	Class 2
12	0.8993	Class 2
13	1.0000	Class 2
14	0.8000	Class 2

Table-8. LPM (Q) Classification by PNN.

BUS	LPM (Q)	PNN Classification
4	2.4991	Class 2
5	2.6828	Class 2
7	1.2221	Class 2
9	1.0576	Class 2
10	0.8962	Class 2
11	0.8412	Class 2
12	0.7037	Class 2
13	0.8357	Class 2
14	0.6370	Class 2

It can be seen from Table-5 until Table-8 that the PNN has successfully classified all of the calculated VSM and LPM values into the right class which is Class 2. As stated in Section 2.4, all values with the differences of ± 0.01 of the calculated VSM/LPM values belong to Class 2.

CONCLUSIONS

The study conducted in this paper has successfully showed the classification of VSM and LPM with the use of probabilistic neural network (PNN). The PNN model used in this research was able to identify which values belong to VSM/LPM and which values that is over or under the calculated VSM/LPM values. The results in Section 3.1 show that Bus 12, Bus 13 and Bus 14 are close towards voltage instability. Hence, actions to avoid voltage instability should be implemented onto these buses.

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